Analysis of Spatial Structure Distribution of Sports Culture Based on Chorography Big Data

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Abstract

The in-depth examination of sports culture's spatial distribution characteristics helps preserve diversity and enhance the transmission and development of regional sports culture. Few academics have studied the spatial distribution of sports culture, and none have exploited chorography big data. To address the void, this paper attempts to improve the spatial distribution structure of sports culture using big data from chorography. Based on chorography big data, the spatial distribution characteristics of sports culture were investigated. Next, the Canopy clustering algorithm and the k-means clustering algorithm were coupled to create the Cartesian k-means (CK-means) clustering algorithm for the concentration areas of sports culture. Unlike the k-means clustering technique, the suggested algorithm does not randomly select anomalous or edge sites as cluster centers, avoiding the local optimum trap. In addition, the algorithm's flow was described. The experimental findings suggest that our algorithm is superior.

Keywords: chorography big data; sports culture; analysis of spatial structure distribution

1. Introduction

China's sports culture materials have deep significance and a lengthy history (Aleksina et al., 2019; Li, 2017; Li, 2022; Wenming, 2021; Zhang, 2019). Sports culture assets belong to both sports and culture. By querying regional chorography, it is possible to obtain an overview of the sports culture resources in a region and to support the transmission and development of regional sports culture with essential data. Thus, the chorography question might significantly enhance the growth of regional sports culture's signature services (Cao et al., 2021; Deng, 2021; He, 2021; Hsieh & Fang, 2021; Huang & Wang, 2021; Weng & Chang, 2017; Xun, 2017; Zhang & Kazerooni, 2016; Zhong & Chen, 2019).

The regional sports culture industry is advancing rapidly in the era of national fitness. Meanwhile, alien cultures impact the traditional sports culture (Jiang & Li, 2020; Li et al., 2021; Liang et al., 2021; Liu, 2014; Wang, 2015; Wang, Li, & Xie, 2014). The spatial distribution and composition of sports culture influence the development pattern of local culture in a region, the economic development of sports culture in the region, and the sports culture service items in the region.

The distinctive folk sports culture on Hainan Island results from the island's superior maritime resources. Ai, Liu, and Lin (2021) investigated the pertinent characteristics of Hainan based on socioeconomic innovation and sustainable development. Wang (2021) analyzed the influence of ethnic minority sports culture in Yunnan and provided recommendations for fostering the development of sports culture in Yunnan within the context of the Belt and Road Initiative. In the era of big data, Yu and Chen (2021) conducted big data research on the interaction between sports and culture using artificial intelligence (AI), highlighting the two-way channel of sports culture. Wu (2021) developed an image recognition system for regular sports video motions that combines local and global aspects. Under the influence of AI, the two-way channel of sports culture was explored using a questionnaire survey and mathematical statistics. Their research accelerates the spread of AI in sports culture and effectively drives the growth of sports culture in China.

With the advent of the era of big data, the transformation and upgrading of the sports industry can be encouraged by the decision-making and scientific development of the sports culture supplies industry. However, the sports stationery market lacks a perfect consumption statistics system. Zhang (2020) merged data mining algorithms, particularly K-means clustering (KMC), fusion decision tree, and Nave Bayes, with data warehousing technology and introduced the integrated technology to the sports stationery business to solve the problem. Using the consumption data system as the object, they grouped the geographical spatial characteristics of consumption in that industry, separated the customers into several classes, and forecasted their purchasing preferences.

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Aleksina, Chernova, and Aleksin (2020) attempted to outline the primary directions of electronic contacts between public management agencies, sports organizations, and service users. The Russian literature on this topic was thoroughly reviewed, and the experience of international researchers was summarized to provide a comprehensive analysis of the digital transformation forms of sports and sports services. The research on the growth law of the sports culture sector lags behind the rapidly expanding sports industry. The backlog severely hinders China's sports business. Therefore, Yang (2020) analyzed the feasibility of predicting the growth of the sports culture industry based on big data theory from the perspective of data mining, proposed a prediction model for the development of that industry based on a genetic neural network, and successfully predicted the growth law of the sports culture industry in the context of big data.

In conclusion, the spatial distribution of sports culture was initially examined in foreign nations. Unsurprisingly, foreign thoughts and practices on this topic are relatively developed. In contrast, Chinese scholars have not extensively investigated the regional dispersion of sports culture. In terms of methodology, domestic research typically uses quantitative methods such as questionnaire surveys but fails to exploit chorography big data.

This paper tries to optimize the spatial distribution structure of sports culture using extensive data from chorography. Based on chorography, Section 2 studies the spatial distribution characteristics of sports culture. Section 3 proposes the Cartesian k-means (CK-means) clustering method for the concentration areas of sports culture and describes the algorithm's flow (Kishore & Rao, 2020). Section 4 analyzes the structure of several sports culture industries through trials and demonstrates that our algorithm is superior to the conventional KMC. Firstly, the spatial distribution features of sports culture were analyzed based on chorography big data. Then, the Cartesian k-means (CK-means) clustering algorithm was designed for the concentration areas of sports culture and the algorithm's flow. Finally, the structure of different sports culture industries was analyzed through experiments. The experimental results demonstrate the superiority of our algorithm.

2. Analysis of Spatial Distribution Features

The sports culture resources in the chorography big data were summarized and sorted out. It was found that different regions share many sports items, yet the cultural connotations of these sports items vary from region to region. The main reason for the variation is the influence of the geographical environment or the integration between traditional sports culture and regional culture. Table 1 lists the common sports items in different regions. The original data were points in all sports culture spaces of the 22 classes of chorography big data in 2016, 2018, and 2020. This paper collects all chorography data from the study area and acquires the literature related to sports culture. Specifically, the authors looked for the books on sports culture in various libraries and queried the literature on traditional sports culture on CNKI, Wanfang Data, and cqvip.com. The chorography data were searched for in specific districts and counties, and the contents about traditional sports culture were sorted and classified.

All the data were checked and categorized according to the class attribute field. Several services that determine the essence of the sports culture industry were thus selected: sports culture retail service, sports culture leisure service, sports culture training service, sports arts, and culture service, and sports fashion and promotion service.

Table 1

Common sports items in different regions

Class	Sports items
Martial arts	Routine sports and combat sports
Archery	Recurve bow, compound bow, and traditional bow
Board games	Go, Chinese chess, military chess, and Chinese checkers
Ethnic minorities' sports items	Sparkler grabbing, pearl ball, wooden ball, kickball, shuttlecock ball, martial arts, wrestling, swing, equestrian sports, crossbow, top whipping, Tibetan tug-of-war, dragon dancing, dragon boating, mountain climbing, jumping, hitting hitching post, rope sliding, rope flying.
Traditional sports items	Lion dancing, traditional kickball, Chinese yo-yo, polo, Chinese hockey, and shuttlecock kicking

Due to the sheer size of chorography big data, the collected sports culture spatial points contain inevitable errors. After coordinate transformation, the data should be visualized before analyzing chorography big data. The abnormal data outside the study area must be de-noised.

If a large region has multiple sports culture spaces, each can be viewed as a point in that region to measure the dispersion of spatial distribution of sports culture. There are three possible spatial distributions of point elements: aggregated, uniform, and random.

Let S be the nearest spatial point index of a point element; s_1^* be the mean of the distance s_1 between the closest points; s_2^* be the theoretical most relative distance; U be the point density. Drawing on the gradual transition of point elements from aggregated distribution to uniform distribution, this paper computes the nearest distance between the components:

$$S = \frac{s_1{}^*}{s_2{}^*} = 2\sqrt{U} \times s_1{}^* \tag{1}$$

If S=1, i.e., $s_1^*=s_2^*$, the point elements are randomly distributed in the sports culture space. If S>1, i.e., $s_1^*>s_2^*$, the point elements are uniformly distributed in the sports culture space. If S<1, i.e., $s_1^*<s_2^*$, the point elements are aggregated and distributed in the sports culture space.

To accurately measure the spatial aggregation degree of sports culture, this paper introduces the geographical concentration index to compute the aggregation degree of the spatial distribution of sports culture in the study area. Let H be the geographical concentration index of the sports culture spaces in the study area; A_i be the number of points in the i-th sports culture space; M be the number of sports culture spaces in the study area; m be the number of subregions of the study area. Then, the geographical concentration index can be calculated by:

$$H = 100 \times \sqrt{\sum_{i=1}^{m} \left(\frac{A_i}{M}\right)^2} \tag{2}$$

In the study area, all chorography big data are correlated. The correlation increases with the decrease in distance. This paper carries out kernel density analysis on the collected data to effectively analyze the spatial distribution of sports culture in the study area. The smooth density surface has the peak density at a spatial point. The surface density gradually reduces with the growing distance from the spatial point on the surface. Once the distance reaches the search radius, the surface density would drop to zero.

Let $L[(1-(a-a_i)^2+(b-b_i)^2/f^2)]^2$ be the kernel density function; (a,b) and (a_i,b_i) be the central point and a point in the neighborhood of the main point; f be the search radius; m be the number of points in the search range. Then, the kernel density formula can be expressed as:

$$g_m(A) = \frac{1}{\pi m f^2} \sum_{i=1}^{m} L\left[\left(1 - \frac{(a-a_i)^2+(b-b_i)^2}{f^2}\right)\right]^2 \tag{3}$$

The standard deviational ellipse model (Figure 1) was developed to precisely measure the direction and distribution of a group of sports culture spatial points. The major and minor axes of the ellipse represent, respectively, the direction distribution and the range distribution of the data. The difference in length between the two axis demonstrates the relevance of data directionality. Let FC_a and FC_b be variances; a_i and b_i be the coordinates of feature i; a^* and b^* be the mean centers of features; m be the total number of features. Then, the size of the ellipse can be determined by FC_a and FC_b:

$$FC_a = \sqrt{\frac{\sum_{i=1}^{m}(a_i-a^*)^2}{m}}, FC_b = \sqrt{\frac{\sum_{i=1}^{m}(b_i-b^*)^2}{m}} \tag{4}$$

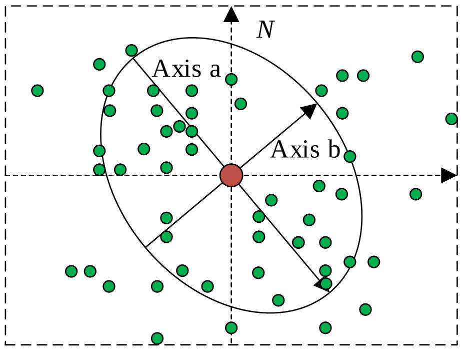

Figure 1. Standard deviational ellipse model

The direction and range of the ellipse depend on axes a and b. Let $\dot{a}_i$ and $\dot{b}_i$ be the deviation of the coordinates of a and b from the mean centers, respectively. Then, the rotation angle can be calculated by:

$$tan\omega = \frac{X+Y}{Z} \tag{5}$$

$$X = \left(\sum_{i=1}^{m} \dot{a}_i^2 - \sum_{i=1}^{m} \dot{b}_i^2\right)$$

$$Y = \sqrt{\left(\sum_{i=1}^{m} \dot{a}_i^2 - \sum_{i=1}^{m} \dot{b}_i^2\right)^2 + 4\left(\sum_{i=1}^{m} \dot{a}_i \dot{b}_i\right)^2}$$

$$Z = 2\sum_{i=1}^{m} \dot{a}_i \dot{b}_i \tag{6}$$

To detect the differentiation between sports culture spaces and disclose the drivers of spatial expansion, the factor detection, and interaction detection methods were employed to recognize the interaction between the five services that affect the spatial clustering of sports culture in the study area. Let A and B be the factors affecting sports culture's spatial expansion and attribute, respectively. The spatial differentiation of B was tested by factor detection. A's ability to explain B's degree of spatial differentiation was also detected. Let f be the class of B or A; M_f and M be the number of units in class f and sports culture spaces in the entire area, respectively; γ^2_f and γ^2 be the variance of class f and the whole-area B value, respectively. Then, we have:

$$w = 1 - \frac{\sum_{f=1}^{K} M_f \gamma_f^2}{M\gamma^2} \tag{7}$$

As shown in formula (7), w falls in the value range of [0, 1]. The greater the w value, the more prominent the spatial differentiation of B. Let μ be the non-centrality parameter; $\dot{B}_f$ is the mean of class f. Then, the transform of w satisfies the non-central F distribution:

$$FD = \frac{M-K}{K-1}\frac{w}{1-w} \sim FD(K-1, M-1; \mu) \quad (8)$$

$$\mu = \frac{1}{\gamma^2}\left[\sum_{f=1}^{K} \dot{B}_f^2 - \frac{1}{M}\left(\sum_{f=1}^{K}\sqrt{M_f}\dot{B}_f\right)^2\right] \quad (9)$$

The interaction detection method was introduced to recognize the interaction between different influencing factors A_r. Firstly, the w values of influencing factors A_1 and A_2 relative to B were solved, namely, $w(A_1)$ and $w(A_2)$. Then, the w value of the interaction between the two factors was calculated, i.e., $q(X_1 \cap X_2) w(A_1 \cap A_2)$. Finally, $w(A_1)$ and $w(A_2)$ were compared with $w(A_1 \cap A_2)$.

Furthermore, global and local spatial autocorrelation indices were employed to explore the clustering level of the observational variables for the factors affecting the sports culture spaces in the study area and to evaluate the degree of differentiation between unit elements in different sports culture spaces. Let M be the number of sports culture spaces in the study area; A_i and A_j be the observed values of the same influencing factor in sports culture spaces *i* and *j*, respectively; $\bar{A}$ be the mean observed value of A_i; θ_{ij} be the spatial weight matrix ($M \times M$) of A_i; R_0 be the sum of spatial weight matrices. Then, the global spatial autocorrelation index can be calculated by:

$$MI = \frac{M}{R_0} \times \frac{\sum_{i=1}^{M}\sum_{j=1}^{M}\theta_{ij}(A_i-\bar{A})(A_j-\bar{A})}{\sum_{i=1}^{M}(A_i-\bar{A})^2} \quad (10)$$

The global spatial autocorrelation index ranges in [-1, 1]. If the index is significantly positive, then the sports culture of the study area clusters significantly in space at the given significance level of $P<0.05$. The closer the index is to 1, the weaker the spatial difference of sports culture. The further away the index is from 1, the stronger the spatial difference of sports culture. If the index is significantly negative, then the sports culture of the study area varies considerably in space at the given significance level. The closer the index is to -1, the more significant the spatial difference in sports culture. If the index equals zero, then the sports culture in the study area is randomly distributed in space without any spatial correlation.

Let C_i and C_j be the normalized values of the observed value of the same influencing factor in sports culture spaces *i* and *j*, respectively; Q_{ij} be the row normalization of spatial weights. Then, the local spatial autocorrelation index can be calculated by:

$$MI_i = C_i \sum_{i=1}^{M} Q_{ij} C_j \quad (11)$$

If both MI_i and C_i are than 0, the observed values of influencing factor at sports culture spatial point i and surrounding points are both high, i.e., the region is a high-high clustering area of sports culture. If $MI_i>0$, and $C_i<0$, the observed value of the influencing factor at sports culture spatial point i is greater than that at surrounding points, i.e., the region is a low-high clustering area of sports culture. If $MI_i<0$, and $C_i>0$, the observed value of influencing factor at sports culture spatial point i is smaller than that at surrounding points, i.e., the region is a high-low clustering area of sports culture. If both MI_i and C_i are smaller than 0, the observed values of influencing factor at sports culture spatial point i and at surrounding points are both low, i.e., the region is a low-low clustering area of sports culture.

3. Spatiotemporal Law

Domestic research on traditional sports culture's spatiotemporal distribution predominantly reveals the distribution status, pattern, and law of traditional sports culture at various scales. On a macroscopic scale, examples of chorography on various scales were used to investigate the distribution status, show the condition and pattern of spatiotemporal distribution, and offer recommendations for the preservation and development of traditional sports culture. This research creates the CK-means clustering algorithm based on the Canopy clustering algorithm and KMC to accurately mine the spatial law of sports culture in the study area from chorography big data. Specifically, the Canopy clustering technique determines the initial cluster center of sports culture spatial points. The initialization of the cluster center addresses a significant flaw of the KMC: the KMC is susceptible to falling into a local optimum because it may randomly select aberrant or edge sites as cluster centers. Faced with the concentration region of sports culture, the CK-means method can be implemented as follows:

Step 1: Enter all sports culture spatial points of the study area into the 22 classes of the chorography extensive data and import the thresholds 1 and 2 of the Canopy clustering method. Select a sports culture spatial point as the cluster center of the Canopy clustering method and then remove the point from the set of sports culture spatial points.

Step 2. Compute the Euclidean distance between the spatial points of the remaining sports culture and the cluster's center. If the result is less than 1, the point is added to the Canopy cluster. If the result is larger than 1, a new Canopy cluster is created for the sports culture spatial points. Let ai, and bi represents sports culture spatial points, and let m represent the total number of sports culture spatial points. Then we have:

$$\varphi(a,b) = \sqrt{\sum_{i=1}^{m}(a_i - b_i)^2} \quad (12)$$

Step 3. If the distance from a sports culture spatial point to any Canopy cluster center is smaller than δ_2, add the point to the corresponding Canopy cluster, and remove the point from the dataset.

Step 4. Implement the previous two stages until all sports culture spatial points are assigned to their respective Canopy clusters. Terminate the process and output the resulting Canopy clusters.

Step 5: Compare all sports culture spatial points with Canopy cluster centers and assign each point to the cluster with the closest cluster center.
Step 6. In each cluster, compute the mean of intra-cluster sports culture spatial locations and use the result as the KMC center.
Step 7. Implement the previous two steps until the variation of the KMC center falls below the preset threshold or the number of iterations reaches the maximum. Let L be the number of clusters; λ_i be the new center of a cluster; u_i be the original cluster center. Then, the judgment criterion can be expressed as:

$$FQ = \sum_{i=1}^{L}(\lambda_i - u_i)^2 \tag{13}$$

Figure 2 shows the flow of the CK-means clustering algorithm for the concentration area of sports culture.

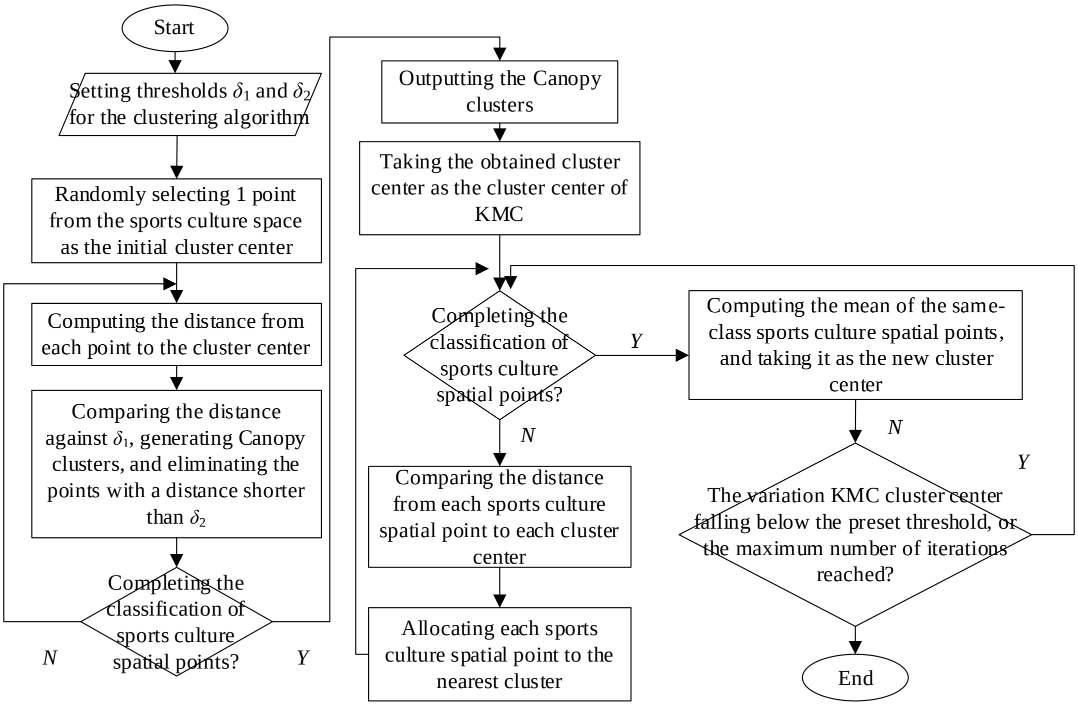

Figure 2. The flow of our clustering algorithm

4. Experiments and Results Analysis

Table 2

Classes and structures of sports culture

Class/level	State-level	Provincial-level	Municipal-level	Total	Proportion (%)
Sports culture shopping service	2	16	22	40	10.89
Sports culture leisure service	5	12	36	53	14.44
Sports culture training service	3	4	7	14	3.81
Sports arts and culture service	6	1	5	12	3.27
Sports fashion and promotion service	17	82	142	241	65.66
Other	2	3	2	7	1.9
Total	35	118	214	367	/
Proportion (%)	9.54	32.15	58.31	/	100%

This paper divides sports culture spatial units into sports culture shopping service, sports culture leisure service, sports culture training service, sports arts and culture service, and sports fashion and promotion service. Table 2 shows the classes and structures of sports culture. Statistics show that the study area has the following sports culture spatial units above the municipal level: 40 sports culture shopping service points; 53 sports culture leisure service points; 14 sports culture training service points; 12 sports arts and culture service points; 241 sports fashion and promotion service points; 7 other points. Overall, sports fashion and promotion services occupy the most in the study area (65.66%). Meanwhile, 10.89%, 14.44%, 3.81%, and 3.27% sports culture spatial units belong to sports culture shopping service, leisure service, training service, and arts and culture service. Only 1.9% belong to the class of other.

The types and structures of sports items in the study region are presented in Table 3. The results indicate that the sports items in the research region can be categorized into three levels. The first level features 82 things (75.92 percent) in non-conventional sports, including martial arts, archery, and board games. The second level consists of sixteen (14.81%) local traditional sports items. The third level consists of ten sports items from ethnic minorities, accounting for 9.25 percent of all sports items in the study area. The share of non-conventional sports items was thirteen times bigger than that of ethnic minority sports items, showing a substantial structural difference between sports items in the research area.

Table 3

Classes and structures of sports items

Class/level	State-level	Provincial-level	Municipal-level	Total	Proportion (%)
Martial arts	5	2	42	49	45.37
Archery	3	0	14	17	15.74
Board games	6	4	6	16	14.81
Ethnic minorities' sports items	2	6	2	10	9.25
Traditional sports items	7	2	7	16	14.81
Total	23	14	71	108	/
Proportion (%)	21.29	12.96	65.74	/	100%

Table 4

Density of sports culture spaces

Region number	Quantity (items)	Proportion (%)	Area (10,000/km^2)	Density (item/10,000 km^2)
1	19	3.82	0.015	4628
2	36	7.18	0.048	2653.27
3	94	22.64	0.062	1628.49
4	52	14.85	0.097	3128.74
5	13	3.62	0.065	1463.51
6	36	8.57	0.079	332.85
7	59	12.69	0.167	302.83
8	82	18.47	0.612	185.92
9	53	13.68	0.274	162.72

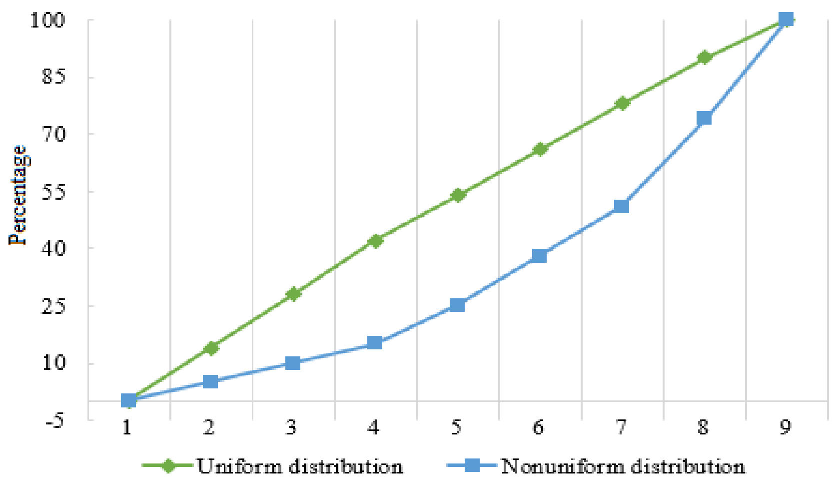

Figure 3. Lorentz curve of the spatial distribution of sports culture in the study area

Referring to the distribution state of sports culture resources in the chorography of Jiangsu and Anhui, Table 4 shows the distribution density of sports culture spaces in the study area. It can be seen that the mean density of sports culture spaces in the study area was 1,588.29 items / 10,000 km^2. Four regions surpassed the mean density: regions 1-4. The highest density was observed in region 1 (4,628 items / 10,000 km^2), and the lowest was observed in region 9 (162.72 items / 10,000 km^2). On the macroscale, the sports culture spaces in the study area distribute differently between regions: the spatial distribution is aggregated in the main urban areas and dispersed in suburban counties and districts.

To further quantify the degree of balance of the spatial distribution of culture in the study area, the Lorentz curve of the spatial distribution of sports culture in the study area was plotted with the subregions as the abscissa and the cumulative proportion of sports culture spaces as the ordinate (Figure 3). The straight lines represent the optimal distribution of sports cultural spaces. The Lorentz curve is concave, showing a geographical imbalance in the distribution of sports culture spaces in the studied area.

Table 5 displays the classification accuracy before and after algorithm optimization. Under the same amount of iterations, the proposed clustering algorithm proved more accurate than the conventional KMC. Therefore, it is effective to optimize the initial cluster center of KMC using the Canopy clustering algorithm. The optimized method has a distinct advantage when examining the concentration zone of sports culture spaces.

Since our algorithm targets the sports cultural resources in chorography big data, data processing is dependent on algorithm performance and data usage. Therefore, this study evaluates the parallelization efficiency of our approach and the parallelization performance on large data sets. Two indices were selected: the speed-up ratio and the expansion ratio. Figures 4 and 5 depict the test outcomes.

As shown in Figure 4, the speed-up ratios for Datasets 1 and 2 did not increase much as the number of sports culture spatial points increased, and both reached 1. In contrast, the speed-up ratios for Datasets 3 and 4 skyrocketed as the number of sports culture spatial points increased. Consequently, our clustering approach is more effective in chorography big data under the Hadoop and Spark frameworks.

Table 5

Classification accuracies before and after the algorithm optimization

Dataset	KMC	Our algorithm
1	7358.59	5248.73
2	41523.74	37258.28
3	17635.42	127484.05
4	212526.95	229581.63

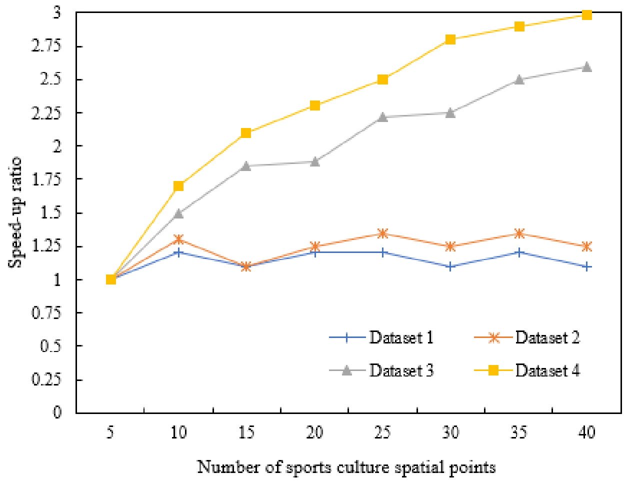

Figure 4. Speed-up ratios of our algorithm

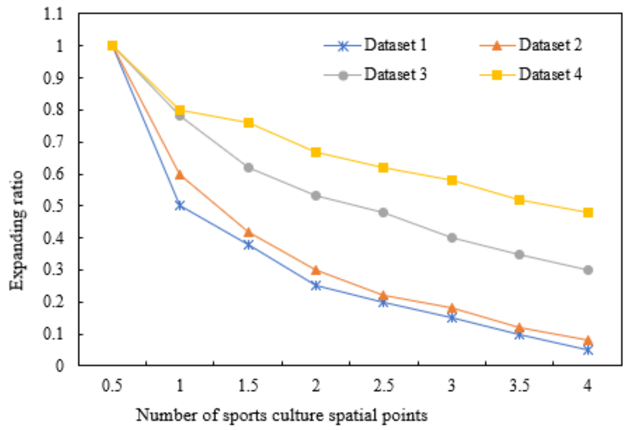

Figure 5. Expanding ratios of our algorithm

Figure 5 illustrates the expanding ratios of our algorithm on four sample sets of sports culture spatial points, based on chorography big data under Hadoop and Spark frameworks. It can be seen that with the growing size of chorography big data and the number of sports culture spatial points, the expanding ratio of every dataset gradually declined and tended to be stable, and the declining speed slowly slowed down. The fastest decline was observed on Dataset 1. Thus, our algorithm boasts a good expansibility on chorography big data, but the expansibility is relatively poor on small datasets. The algorithm has sufficient expansibility for big data parallelization.

5. Conclusions

This paper improves the spatial distribution structure of sports culture based on chorography big data. After researching the spatial distribution characteristics of sports culture, the authors created the CK-means clustering method for the concentration areas of sports culture and clarified the algorithm's flow. The authors conducted experiments to evaluate the classes and structures of sports culture industries, the classes and structures of sports products, and the densities of sports culture venues. Then, the Lorentz curve was plotted for the spatial distribution of sports culture in the study area, indicating the unbalanced distribution of such spaces in the study area. In addition, classification accuracy before and after algorithm optimization was evaluated. The canopy clustering algorithm effectively optimizes the initial cluster center of KMC. In addition, the speed-up ratio and expanding ratio were used to evaluate the parallelization efficiency of our technique and the parallelization performance on massive data. Our clustering approach is more effective and highly scalable on chorography big data under the Hadoop and Spark frameworks.

This article examines the regional sports culture resources in light of regional chorography records. Theoretically, the chorography-based analysis of the spatiotemporal distribution of regional sports culture blends history and sports studies and presents fresh theories for sports culture research. Practically, this research enriches regional sports culture resources, promotes the development of regional sports culture and traditional culture, enables the regions to close the economic gap with developed regions, and provides a reference for promoting local construction and representative regional cultural brands.

This research must be improved and expanded in the following ways: First, the spatial-temporal dispersion of sports culture is simultaneously influenced by numerous causes. However, this paper only examines reasonably frequent causes. Quantitative data proved their spatial distribution, while their temporal distribution was analyzed qualitatively. The reasonableness of the presentation and examination must be checked. Second, the issues in the protection and development of regional sports culture are primarily highlighted based on our results, and the solutions are the result of our subjective evaluations. This research discusses these concerns, which encompass several fields, only subjectively. Future surveys and studies must be more comprehensive.

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